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An optimization model for regional renewable energy development

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ABSTRACT

This research effort details the modeling component of a comprehensive decision support system for energy planning that allows for combining existing electricity generating capabilities with increased use of renewable energy sources. It focuses on energy planning at the regional level, and it is illustrated by applying it to the greater southern Appalachian mountains of the eastern United States: a region that was chosen for analysis not only due to its heavy dependence on coal for electricity, but also because of its potential for increased use of wind and solar power. The paper specifically discusses the development of a multi-objective linear programming (MOLP) model that can be used to determine the optimal mix of renewable energy sources and existing fossil fuel facilities on a regional basis. This model allows a decision maker to balance annual generation costs against the corresponding greenhouse gas emissions, and it provides significant support for implementing a variety of different policy analyses.

Contents

1. Introduction

Renewable energy sources are well recognized as an essential component of efforts to reduce carbon emissions worldwide. In particular, renewable energy development can serve as a mechanism to reduce the environmental impacts of energy consumption, to improve the local economy, and to increase community participation in local environmental management [1,2]. A great deal of research has been devoted to different techniques focused specifically on improving renewable energy planning at the regional level. Developing nations, such as India [3] or China [4], are often studied in this context because the use of renewable energy sources helps create sustainable communities, and in many cases these electrification efforts are the first attempts to bring electricity to these regions. The EU also has been the subject of much of this research because of regulations requiring increases in

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renewable energy sources as a percentage of overall power supply [5].

Research into renewable energy sources in the United States, such as that performed at the National Renewable Energy Laboratory (NREL) in Golden, Colorado, has primarily focused on exploring potential energy sources at the national level. As such, it typically has considered the issue at a higher level of aggregation than in other countries [6]. It is important, however, to also consider renewable energy from a regional standpoint, since the characteristics of different parts of the United States are often distinct, both from the standpoint of resource availability and political climate. A good example of this is the greater southern Appalachian Mountains: this particular region is heavily dependent on coal for energy, but it also has good renewable energy potential.

Throughout the literature, a variety of different analytical techniques have been used to model the generation and distribution of electricity. These have included multi-objective approaches such as multicriteria decision making [7–10] and the analytic hierarchy process [4,11], but they have also included mathematical programming techniques. Mathematical programming has been used frequently for energy planning, and in a number of different contexts such as minimizing capital investment in new energy sources [12], minimizing costs of energy flows [3,13,14], and maximizing renewable energy usage [15]. Comprehensive models also have been developed through the use of multi-objective linear programming [16–21] and goal programming [22–24]. Several comprehensive reviews of mathematical programming techniques for renewable energy systems have recently been published [25,26].

It is important to note that these existing models have all been developed independently of the research on identifying potential renewable energy sources using geographic information systems (GIS). When necessary, these models have tended to contain simple estimates related to the potential renewable energy source, or sources, but they include limited discussion of the origin of these numbers, and most often they are derived from outside research and resources. The numbers thus may neither reflect the reality of the situation, nor properly consider the validity of the data sources.

With this in mind, the research effort described here is part of an effort to combine validated data sources with advanced modeling capabilities in order to provide a comprehensive analysis of renewable energy potential at the regional level. The current discussion centers around a mixed-integer, multi-objective optimization model that supports examining the tradeoffs between conflicting objectives related to environmental and economic concerns [27–29]. The optimization model is directly integrated with a regionally-focused GIS model, and it provides the user with the opportunity to adjust various parameter values in support of better understanding potential outcomes associated with different environmental or budgetary constraints. This integrated model can then support the comparative analysis of different public policies, with respect to both cost effectiveness and level of emissions.

Our detailed discussion of this optimization model exists within the context of the three components of a comprehensive decision support system for regional renewable energy planning: (1) a regionally-focused GIS model for data collection; (2) an optimization model for determining the most effective usage of resources under constrained conditions; and (3) a policy analysis decision making framework. A detailed look at the first of these components was provided by Arnette and Zobel [30], in the context of the greater southern Appalachian mountain region. Arnette and Zobel [31] then provided an in-depth discussion of the third component that considers the relative effects of applying three potential public policies within this same region: a renewable portfolio standard, a carbon tax, and a renewable energy production tax credit. This paper complements and enhances these other efforts by explicitly providing the formal details of the most important component of the system: the optimization model.

We begin the paper with a discussion of the greater southern Appalachian region, and provide a brief description of the underlying GIS model as applied in this context. We then define the optimization model, and discuss different aspects of its formulation in detail. The paper continues by considering some illustrative test results, in the context of the chosen region and the tradeoffs between the different objectives. We conclude the discussion by considering the flexibility of the model and by discussing its ability to be adapted to a variety of different contexts.

2. Background

The greater southern Appalachian mountain (GSAM) region of the United States is comprised of portions of Kentucky, North Carolina, Tennessee, Virginia, and West Virginia (Fig. 1). As mentioned above, this region was selected for two major reasons: first, it is home to some of the best on-shore wind potential in the Eastern United States; and second, it is heavily dependent on the use of coal for generation of electricity. Electricity generated from coal at coal-only plants and coal/biomass co-fire facilities comprises 84.39% of the total generation (Table 1) in the region, whereas nationwide, coal generates only 48.2% of all electricity [32]. Because total renewable generation in the region is only 3.37% of the total [30], there is potential opportunity for increasing the use of renewable energy from sources such as wind, solar, and biomass.

The dependence of the greater southern Appalachian region on coal has also resulted in large quantities of greenhouse gas

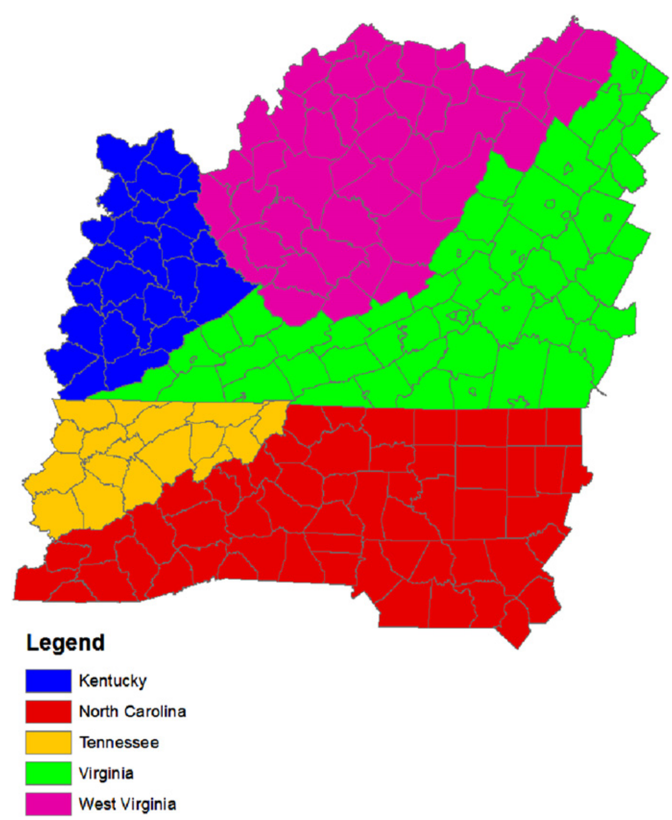


Fig. 1. Greater Southern Appalachian Mountain region.

Table 1
Generation by source within region.

Source	Number of facilities	MWh generated	Percentage of total generation (%)
Coal	31	165,721,345	83.50
Nuclear	1	17,619,492	8.88
Gas	13	6,449,095	3.25
Water	69	4,981,292	2.51
Co-fire	4	2,188,456	1.10
Biomass	3	1,026,986	0.52
Oil	22	241,841	0.12
Wind	1	167,588	0.08
Landfill	4	78,071	0.04

Table 2
Tons of emissions of greenhouse gases within the region.

	Emissions from coal plants	Emissions from other facilities	Total emissions
CO_2	163,055,697	2,504,204	165,559,901
SO_2	859,587	1,524	861,110
NO_X	253,350	1,500	254,951

emissions. In particular, the emissions of the three gases analyzed in this model (CO_2, SO_2, and NO_X) are estimated at 166.68 million tons annually, with 99.3% of emissions derived from coal-only plants (Table 2) [33].

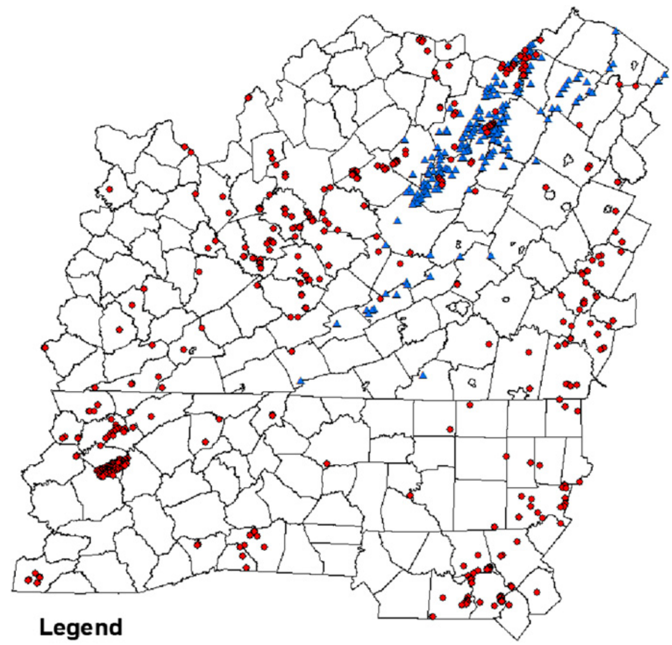


Fig. 2. Potential wind and solar farm sites within the region.

2.1. Determining wind and solar potential

To determine the potential locations for large-scale wind and solar farm sites within the region, a GIS model was developed in ESRI's ArcMap 9.3.1 software [30,34]. The site locations were identified based on constraints derived from geographic and atmospheric conditions, as well as constraints due to land use restrictions, conservation limitations, and other regulations. The focus of the model was on large-scale installations managed by utility companies, rather than on distributed generation by homeowners or other end-users, because the willingness of end-users to invest is largely unknown; and the estimation of urban land that can be realistically utilized has not been fully explored in practice.

The primary initial measure used for the discovery of potential solar farm locations was *solar insolation*, an indication of the amount of solar radiation received on the Earth's surface as developed by NREL [35]. Average annual values for this metric range from 4194.1–5006.5 kWh/m^2/day within the region under consideration; this is considered "good" by the NREL, in terms of potential for solar energy usage. Data from the National Elevation Dataset (NED) [36] was then used to eliminate specific locations based on the slope and aspect of each potential site, and sites were further restricted by allowing only non-agricultural barren land [37], and by incorporating other land use restrictions associated with regulations and protections in place [38].

Potential wind farm locations were derived in a similar manner, using many of the same data sources but with different restrictions. The base data set for wind power was developed by NREL [35], synthesizing previous meteorological, satellite, and ground cover datasets. NREL classifies each location with a wind power value between 0 ("poor") and 7 ("superb"), where values of 3 or greater are considered acceptable for wind farm development. Only 2.38% of the land within the region met this constraint. Constraints were also placed on potential wind locations based on slope values, land uses, and restrictions and protections on land areas. Furthermore, buffers representing a minimum distance that a wind farm location must be from a previously constrained area were also defined. Such buffers are typical, due to the visible nature of wind turbines, as well as the noise generated and possible interference with wildlife [5,6,39,40].

After eliminating sites that would be too small to be cost-effective, the GIS model generated a total of 203 potential wind farm sites and 477 potential solar farm sites within the region (Fig. 2), representing the potential to replace 3.24% and 3.33% of baseline generation requirements, respectively.

2.2. Other resources

In addition to wind and solar resources, the current model also consides the possibility of implementing biomass co-fire at existing coal plants. Biomass co-fire is recognized as a cost-effective way to reduce emissions and to increase renewable energy generation [41,42], and the cost to retrofit coal plants for lower levels of co-fire is less than that to create new dedicated biomass facilities. Recent research has shown the potential impact that co-fire can have in reducing emissions and facilitating the transition from fossil fuel-dominated generation to a more sustainable future [43,44]. Biomass data is provided at the county level, and the region currently has an estimated 9.57 million tons of solid wood waste within the region [35] that can be utilized for co-fire at coal plants. Because other forms of biomass cannot be used in co-fire implementations, or are much more expensive to implement, only solid wood waste of various forms (urban, mill residue, and forest residue) is considered in this model.

The baseline power generation data indicates the utilization of a total of 67.17 T of coal [45]. Since solid wood waste biomass is estimated to have an efficiency of 61% per ton in comparison to a ton of coal [46], approximately 8.7% of the coal utilized in this region could therefore be replaced with such biomass by implementing biomass co-firing at existing coal plants. The actual replacement of coal with biomass, however, will vary with the efficiency of the plants selected for co-fire.

3. Model formulation

Although the GIS model can indicate the overall potential for installing renewable resources, a more robust approach is necessary to fully explore the relationships between potential sites and to choose the optimal combination of locations and resource types subject to constraints on available resources. The remainder of the discussion therefore involves the resulting development of a mixed-integer, multi-objective optimization model for regional renewable energy planning.

The inputs into this multi-objective model are the GIS-derived characteristics of each potential location, such as the resource potential, area, land uses, slope, aspect, and new transmission line requirements. The model then seeks to simultaneously minimize both the environmental impact and the overall energy generation costs associated with implementing the chosen renewable resources: large-scale wind and solar farms, and biomass co-fire at existing coal-burning power plants.

The environmental impact of a given solution is measured in terms of total emissions of CO_2, SO_2, and NO_X within the region. The model allows for decreasing generation at existing coal plants and for converting them to biomass and coal co-fire facilities, but it attempts to meet any growth in demand through wind and solar farms, and not through the creation of new coal-only facilities. Since such efforts to decrease emissions come at a cost, the model also considers the additional (and competing) objective of minimizing annual system operating costs.

3.1. Decision variables

Suppose that

N_w the number of possible wind farm locations in the GSAM region,
N_s the number of possible solar farm locations in the region,
N_{ct} the number of counties in the region,
N_c the number of existing coal-based electricity generating plants in the region, and
N_{nc} the number of existing non-coal-based electricity generating plants in the region.

We may then define the decision variables used in the model, as follows:

$$W_i = \begin{cases} 1 & \text{if a wind farm is to be placed at location i for } i = 1,\ldots, N_w \\ 0 & \text{otherwise} \end{cases}$$

$$S_j = \begin{cases} 1 & \text{if a solar farm is to be placed at location } j \text{ for } j = 1,\ldots,N_s \\ 0 & \text{otherwise} \end{cases}$$

$B_{yp} \geq 0$=tons of biomass transported between county y and coal plant p, for y=1,…, N_{ct} and p=1,…,N_c
$U_q \in [0,1]$=capacity utilization of existing non-coal electricity generation facility q, relative to baseline levels, for q=1,…,N_{nc}
$G_p \in [0,1]$=capacity utilization of existing coal electricity generation facility p, relative to baseline levels, for p=1,…,N_c

Taken together, the capacity utilization variables Uq and Gp apply to all electricity generating facilities in the region, including coal, oil, gas, nuclear, and hydro facilities as well as existing wind farm facilities and dedicated biomass plants. These variables allow the model to scale back electricity generation at facilities that generate larger amounts of pollution or are more costly to operate, even to the point of closing an existing facility (when utilization=0). As indicated in each case, full capacity utilization is measured with respect to generation in the baseline year, and not necessarily with respect to the full capacity of the plant. For new wind and solar locations, only full utilization is allowed as the capital investment costs associated with preparing a selected location are being divided over lower levels of capacity, increasing the cost of generating electricity at these locations.

3.2. Objectives

The two competing objectives in this model are (1) to minimize the annual electricity generation costs and (2) to minimize total emissions of three greenhouse gases (CO_2, SO_2, NO_X). These objectives must each satisfy minimum electricity generation requirements, and they are subject to constraints on capital investment and resource utilization, as outlined later in the discussion.

3.2.1. Objective 1: minimize cost

The initial two components of the objective function associated with minimizing annual generation costs are related to the cost of producing wind and solar power. Each of these components, in turn, contains three sub-components: capital investment costs, fixed operating and maintenance (O&M) costs, and variable O&M costs. The capital investment costs are amortized over a user-specified number of years, the fixed O&M costs (insurance, property taxes, and site maintenance) are defined relative to the kW capacity installed, and the variable O&M costs (turbine warranties, labor costs, and royalties paid to land owners) are based on the actual MWh generated annually (which we initially assume to be constant). This three-part cost structure is based on the approach taken by the NREL ReEDS model [6].

The corresponding parameters associated with wind and solar farms are then given as

Wind parameter	Solar parameter	Parameter description
C_i^{vw}	C_i^{vs}	Annualized capital investment at location i
C^{kwm}	C^{ksm}	Annual fixed O&M costs per installed kW of capacity
K_i^w	K_i^s	kW capacity at location i
C^{mwm}	C^{msm}	Annual variable O&M costs per MWh of generation
M_i^w	M_i^s	Expected annual MWh generation at location i

The next component of the cost objective function is associated with coal-fired plants being considered for biomass co-fire. The costs associated with these plants include the amortized cost of the capital investment for co-fire retrofit at each facility selected for biomass implementation, as well as the cost per ton of coal and cost per ton of biomass utilized at the plant. There is an additional cost per MWh of generation at each plant which represents labor, plant operating costs, and other costs not directly accounted for elsewhere in the model. Finally, there is a cost associated with transporting a ton of biomass for one mile. By estimating the distance between the center of each county and each coal plant, this cost penalty is used to minimize biomass transport by encouraging consumption of biomass closest to where the fuels are located. An additional parameter is also introduced, representing the efficiency of biomass versus coal, which is derived from previous research [46].

The parameters associated with the coal-fired plants are thus specified as follows:

C_p^{vc} annualized capital investment for co-fire retrofit at coal plant p
C^{tc} cost per ton of coal

C^{tb} cost per ton of biomass
C^{tbd} cost of transporting one ton of biomass one mile
D_{yp} estimated distance between county y and coal plant p
C^{ac} additional cost per MWh generated at a coal plant, including labor, operating, etc.
M_p^c MWh generated at coal plant p in baseline year
T_p tons of coal used at coal plant p in baseline year

Finally, there are costs associated with each *existing* non-coal facility. The costs for electricity generation at each such facility are estimated on the basis of annual MWh generated. The model does not utilize direct fuel costs, but is based on a cost for each non-coal fuel type that includes fuel costs, plant operating costs, labor, and more. These costs are assumed constant throughout the region and are based on fuel type

C_q^{mn} cost per MWh generated at non-coal facility q
M_q^n MWh generated at non-coal facility q in baseline year

Given these parameters and the decision variables defined above, we may then represent the objective function for annual electricity generation costs as follows:

$$f_{cost} = \sum_{i=1}^{N_i} W_i(C_i^{vw} + C^{kwm}K_i^w + C^{mwm}M_i^w) + \sum_{j=1}^{N_j} S_j(C_j^{vs} + C^{ksm}K_j^s + C^{msm}M_j^s) + \sum_{p=1}^{N_p}\left\{(C_p^{vc} + C^{ac}G_pM_p^c + C^{tc}G_pT_p) + \sum_{y=1}^{N_y}(C^{tb}B_{yp} + C^{tbd}B_{yp}D_{yp} - C^{tc}B_{yp}F)\right\} + \sum_{q=1}^{N_q} C_q^{mn}M_q^nU_q \quad (1)$$

3.2.2. Objective 2: minimize emissions

The second objective, to minimize emissions, uses data from the U.S. Department of Energy [45] on MWh production, and uses emissions data taken from the U.S. Environmental Protection Agency's eGRID report [33]. Based on previous research, the objective function assumes a linear relationship between the amount of electricity generated at a facility and the amount of emissions [41]. The calculation for emissions at coal plants, whether the plant is coal only or coal-biomass co-fire, is based on tons of input, while the calculation of emissions at all existing non-coal facilities is based on the MWh generated in the baseline year and the capacity utilization decision variable.

Different parameters are used to represent the emissions of greenhouse gases associated with electricity generation from coal, biomass, and non-coal sources. In each case, three types of greenhouse gases are considered: CO_2, SO_2, and NO_X. The parameters are as follows:

Coal	Non-coal	biomass	Parameter description
E_i^{co-p}	E_i^{co-q}	E_i^{co-b}	Tons of CO_2 emissions at facility i*
E_i^{so-p}	E_i^{so-q}	E_i^{so-b}	Tons of SO_2 emissions at facility i*
E_i^{no-p}	E_i^{no-q}	E_i^{no-b}	Tons of NO_X emissions at facility i*

* is per ton of coal or biomass used, or per MWh of generation by non-coal sources.

The biomass parameter values used in the model are constant, regardless of which plant is being considered, based on previous research and pilot programs [41,42,46], and they are calculated as one minus the reduction in emissions per ton of biomass. For example, if the user specifies a 15% reduction in NO_X emissions as compared to those due to one ton of coal, then the value of E_p^{no-b} for each plant would be 85% of the rate of emissions for one ton of coal at that coal plant.

The objective function for total greenhouse gas emissions is then given by

$$f_{emissions} = \sum_{p=1}^{N_p}\left\{([E_p^{co-p} + E_p^{so-p} + E_p^{no-p}]G_pT_p)) - \sum_{y=1}^{N_y}([E_p^{co-p} + E_p^{so-p} + E_p^{no-p}]B_{yp}F + [E_p^{co-b} + E_p^{so-b} + E_p^{no-b}]B_{yp}\right\} + \sum_{q=1}^{N_q}[E_q^{co-q} + E_q^{so-q} + E_q^{no-q}]M_q^nU_q \quad (2)$$

3.2.3. Constraints

There are also a number of constraints incorporated into the model to restrict the set of feasible solutions. The first of these requires that the total tons of biomass transported from county y to all plants not exceed the tons of biomass available within the county (B_y^{avail}).

$$\sum_{p=1}^{N_p} B_{yp} \le B_y^{avail} \quad (3)$$

The second constraint specifies that the amount of biomass cannot exceed a specified percentage of total fuel generation without requiring major modifications to the plant [42,46]. As each ton of biomass does not generate as much electricity as a ton of coal, the constraint is based on the amount of electricity generated through the use of biomass, not a percentage of total tonnage consumed at the plant. The parameter X, which is equal to the percentage of total fuel generating tons that can be derived from biomass, is introduced in this equation.

$$\sum_{y=1}^{N_y} B_{yp}F \le G_pT_pX \quad (4)$$

The third constraint is that the total amount of electricity generation, in terms of MWh/year, must meet or exceed total demand for electricity within the region. Electricity generation planning requires estimating electricity consumption for future time periods. In this model, the user can determine the amount of electricity needed based on a growth factor, defined as H, that is multiplied by the baseline MWh generated within the region, defined in the model as M^{base}. This allows the user to have some flexibility in planning and does not lock them into a model that only plans for a certain number of years in the future.

$$\sum_{i=1}^{N_i} M_i^wW_i + \sum_{j=1}^{N_j} M_j^sS_j + \sum_{p=1}^{N_p} M_p^cG_p + \sum_{q=1}^{N_q} M_q^nU_q \ge M^{base}(1+H) \quad (5)$$

The fourth constraint is for the total amount of capital investment allowed in the model. Many of the previous models have sought only to minimize total electricity generation costs without considering the amount of money that is available for capital investment at the time. Therefore many models may produce results that prescribe increased levels of wind and solar electricity generation, but the up-front capital investment funds may not be sufficient to meet the levels of new wind and solar capacity. Including this constraint will allow the user to experiment with different capital investment levels to determine the mix of resources given the constraint on these funds and to analyze different investment scenarios.

While the capital cost of installing solar is based solely on the amount of capacity installed, wind farm locations carry some additional costs. The first additional cost is due to the fact that wind farms can be installed on forest land which requires

clearing, while solar farms were not permitted on forest land in the GIS model. The second additional cost for wind farm development is a penalty on the average slope at a wind farm location. Mild slopes can be beneficial to the development of a solar farm location, but these slopes require additional land preparation and installation costs for wind turbines. The capital investment costs associated with kW of capacity for wind and solar include all equipment, basic installation, and interconnection fees and are assumed linear, as is the installation cost per degree of slope. This approach to calculating costs has been used in previous models [6,47].

The costs and associated parameters for the fourth constraint are thus defined as follows:

C^{kw} cost of installing one kW of wind capacity
C^{af} cost of clearing one acre of forest land for wind farm installation
A_i^f acres of forested land at wind farm location i
C^l cost per degree of slope at wind farm location
L_i average degree of slope at wind farm location i
C^{ks} cost of installing one kW of solar capacity
C^{kb} cost of retrofitting a coal-fired plant for biomass co-fire per kW of capacity
K_p^c overall kW capacity at coal plant p
M_p^{tc} MWh generated per ton of coal in baseline year at plant p
V total amount of capital investment available

and the constraint on capital investment is given by

$$\sum_{i=1}^{N_i} K_i^w (C^{kw} + C^{af} A_i^f + C^l L_i) + \sum_{j=1}^{N_j} C^{ks} K_j^s + \sum_{p=1}^{N_p} \left[C^{kb} (K_p^c / M_p^c) M_p^{tc} \sum_{y=1}^{N_y} B_{yp} F \right] \leq V \quad (6)$$

3.2.4. Parameters

Parameter values can generally be drawn from various government agencies, academic reports, and non-profit organizations [6,32,42,46–53]. In some cases, the estimates provided by these sources vary greatly and an average, or most often cited, value must be used as an estimate within the model. Depending on the size of the region to which the model is applied, more accurate and site specific information may be available for some of the parameters' values.

The calculations for cost and generation require a number of parameters that are specific to the source being analyzed: biomass/coal co-fire (Table 3), wind (Table 4), solar (Table 5), and existing non-coal facility generation (Table 6). Many of these parameters are subject to variability. For example, the cost of a ton of coal has fluctuated greatly in the past few years, and the average cost per ton increased more than 20% between 2007 and 2008 [32]. Due to the changing cost structure of traditional fossil-fuel sources, therefore, the model supports user inputs for specifying the current costs.

The user is also allowed to define the costs and sizing for wind turbines and solar panels. These technologies have been experiencing a rapid decrease in cost, making them more competitive with traditional fuel sources than in the past. The variety of wind turbine and solar panel technologies has been increasing over the last few years as well. Because of this, the model does not lock the user into one type of technology; instead it allows for different inputs to be altered by the user to test the impact that different technologies would have on the model.

Several of the model inputs must be provided solely by the user of the system. In particular, the user must provide the model with specific values that define the right hand side of two of the constraints. The first of these is the value of increased generation required in the model, defined as H, in relation to the baseline generation level. The second user input specifies the maximum amount of capital investment allotted to the model, V. This is a unique and very important constraint in this model, providing the ability to determine the best mix of current and future resources given a limit on investment.

Table 3
Parameters for biomass & coal co-fire.

Parameter	Value	Source[a]
Maximum co-fire % (energy basis)	10%	E, F
Efficiency of ton/biomass vs ton/coal	61%	E
Cost of biomass transport (ton/mile)	$0.25	J
Cost of biomass ($/ton)	$40	D
Cost of coal ($/ton)	$55	D
Capital cost of co-fire retrofit (per kW)	$100	E, F
NOx reduction for biomass %	15%	F
SO2 reduction for biomass %	100%	F
CO2 reduction for biomass %	100%	F
Additional cost per mwh generated at coal plant	$7.50	G

[a] A: [6], B: [48], C: [49], D: [32], E: [46], F: [44], G: [50], H: [51], I: [47], J: [52], K: [53]

Table 4
Parameters for wind farm calculations.

Parameter	Value	Source[a]
Cost of preparing forest land ($/acre)	$5,000	K
Capital cost ($/kW)	$1,570	A
Diameter of wind turbine blades (m)	50	H
Spacing between turbines (# of diameters)	8	H
Electricity conversion factor (%)	25%	I
Fixed O&M ($/kW year)	$10.95	A
Variable O&M ($/MWh)	$5.19	A
Slope penalty (% of capital cost/degree of slope)	2.5%	A
Cost of new transmission lines ($/mile)	$2,000,000	C

Table 5
Parameters for solar farm calculations.

Parameter	Value	Source[a]
Capital cost ($/kW)	$3,480	A
Derate factor (%)	77%	I
Fixed O&M ($/kW year)	$22.00	A
Variable O&M ($/MWh)	$0.00	A
Expected plant life (years)	30	I
Converstion factor (%)	12.5%	I
Cost of new transmission lines ($/mile)	$2,000,000	C

Table 6
Parameters for non-coal facility generation.

Cost of electricity generation by source ($/kWh)	Value	Source[a]
Biomass	$0.05200	B
Co-fire	$0.03000	B, D
Gas	$0.06993	D
Landfill	$0.05200	B
Nuclear	$0.02116	D
Oil	$0.03567	D
Water	$0.00967	D
Wind	$0.06993	D

[a] A: [6], B: [48], C: [49], D: [32], E: [46], F: [44], G: [50], H: [51], I: [47], J: [52], K: [53].

4. Illustrative results

In order to illustrate the model described above, we apply it within the context of the GIS results for the greater southern Appalachian mountain region. Within this particular region, only 6.2% of the baseline levels can be generated through new wind and solar potential. Pushing the value too much higher would require a substantial increase in capital investment, or the model would be required to select all possible sites in order to meet higher growth values.

Using the initial parameters given in Tables 3–6, estimates of the cost for each potential wind and solar farm site were calculated. There is a total estimated capacity of 1.859 GW of wind power that can be installed in this region, which is capable of generating 6.44 MWh annually, or 3.24% of baseline generation in this region. Installing the full capacity of wind power is estimated to cost $13.72 billion, with an average cost at each site of $0.1487/kWh, and a range of $0.0274/kWh–$0.4888/kWh. The capacity of solar power at the potential sites is estimated at 5.08 GW, capable of generating approximately 6.60 MWh annually, which is 3.33% of baseline generation. The cost of full solar implementation given the current GIS model is $32.6 billion at an average of $0.2219/kWh at each site, and a range of $0.1037/kWh–$0.6435/kWh. The range of costs present in both the wind and solar sites is due to the strength of the resource at each site, the size of the site, and the location of the site in relation to the current grid infrastructure. In addition, it is estimated that biomass could replace approximately 8.7% of coal used within the region at a cost of $164.96 million. The estimated capital investment required for meeting all co-fire, wind, and solar development in the chosen region is thus approximately $46.16 billion. A maximum investment value (V) of $15 billion was subsequently specified for the initial analysis, in order to reflect approximately one-third of the maximum total capital investment.

Over the past ten years, the average growth in demand within the region was 0.75%, and thus an increased generation requirement, H, of 2.5% would represent approximately 3 years of growth. This is generally not a long enough time-frame to complete the development of the necessary wind and solar farms. However, the demand values used in the model reflect generation in the baseline year and are not representative of the full capacity of these facilities, therefore any demand fluctuations between the planning stage and the full implementation of the plan are assumed to be met by existing resources. As more investment capital is made available in the model, the ability to meet growth in electricity demand through renewable energy sources will increase.

Utilizing these parameter values, the mixed-integer multi-objective optimization problem was run on the Frontline System Risk Solver Platform in Microsoft Excel [54], on a Pentium 4, 3.2 GHz machine with Microsoft Windows XP. The model for this region consists of 7370 decision variables and 8197 constraints. Given the size of this model, the computing time was relatively small, as each of the five scenarios analyzed in this section were solved in less than 4 min.

The minimax approach was used in order to generate non-dominated, Pareto optimal solutions [55]. The model was thus first run for each of the two objectives individually to determine target solutions, and three additional minimax scenarios (equally weighted, cost-weighted, and emissions-weighted) were then run to illustrate the relative tradeoffs between each of these objectives. A summary of the results of these five basic scenarios is given in Table 7, along with additional summaries focused specifically on biomass/coal co-fire (Table 8), wind (Table 9), and solar (Table 10).

4.1. Cost minimization

The cost objective was first minimized without explicitly considering emissions, and the result was an optimal annual generation cost of $6.25 billion. This solution meets the exact amount of demand specified by the generation constraint, but uses only $6.77 billion of the $15 billion allotted for capital investment. Biomass co-fire at coal plants is not utilized under this cost minimization scenario. Although the use of co-fire can be generally beneficial in decreasing emissions, the increased costs associated with its implementation do not provide extra capacity for generation and only lead to increased cost per unit of power generated at coal plants. The development of new wind farms accounts for 2.19% of generation in this scenario, while solar farm sites provide 0.25% of generation. The total use of renewable energy sources in this scenario is 5.73%, representing a slight increase over the previous 3.37% in baseline generation. Nearly all

Table 7
Overall scenario results summary.

	Minimize cost	Minimize emissions	Minimax—equal weight	Minimax—cost weighted	Minimax—emissions weighted
Total cost	$6,251,629,215	$6,905,758,165	$6,409,560,564	$6,368,243,366	$6,464,037,443
Deviation from target Cost	0.00%	10.46%	2.53%	1.87%	3.40%
Total emissions (tons)	166,550,331	148,597,871	152,351,814	154,141,582	151,122,285
Deviation from target emissions	12.08%	0.00%	2.53%	3.73%	1.70%
Renewable generation	5.73%	14.20%	12.70%	11.79%	13.16%
Capital investment utilization	45.13%	99.99%	46.51%	46.01%	58.75%

Table 8
Scenario results summary for biomass/coal co-fire.

	Minimize cost	Minimize emissions	Minimax—equal weight	Minimax—cost weighted	Minimax—emissions weighted
Number of coal plants using biomass co-fire	0	20	27	26	23
Utilization of biomass resources	0.00%	100%	98.98%	86.02%	100%
Overall generation from biomass	0.00%	7.15%	6.96%	6.07%	7.10%
Total co-fire investment (millions)	$0.00	$168.92	$161.90	$140.94	$165.66
Coal plant generation versus baseline levels	100%	98.39%	100%	100%	99.61%
Reduction in emissions at coal plants versus baseline levels	0.00%	10.92%	8.64%	7.56%	9.37%

Table 9
Scenario results summary for wind.

	Minimize cost	Minimize emissions	Minimax—equal weight	Minimax—cost weighted	Minimax—emissions weighted
Number of sites selected	72	116	73	75	81
Total MW capacity installed	1,245,000	1,486,000	1,251,000	1,262,000	1,303,000
Total capital investment (billions)	$5.419	$7.786	$5.463	$5.581	$5.895
Overall generation from wind	2.19%	2.59%	2.20%	2.23%	2.28%
Average cost per kWh	$0.0550	$0.0654	$0.0552	$0.0558	$0.0572

Table 10
Scenario results summary for solar.

	Minimize cost	Minimize emissions	Minimax—equal weight	Minimax—cost weighted	Minimax—emissions weighted
Number of sites selected	5	73	5	4	20
Total kW capacity installed	370,889	1,787,664	370,889	323,583	748,390
Total capital investment (billions)	$1.351	$7.045	$1.351	$1.181	$2.752
Overall generation from solar	0.25%	1.17%	0.25%	0.21%	0.49%
Average cost per kWh	$0.1065	$0.1153	$0.1065	$0.1064	$0.1080

of the non-coal facilities in the region are utilized at full capacity in this scenario, with only one gas plant operating at 98% of baseline capacity.

4.2. Emissions minimization

In a similar fashion, the emissions objective was also minimized independently from the cost objective. This scenario resulted in 148.6 total million tons of emissions, based on the underlying GIS model, the constraint on capital investment availability, and the anticipated growth in demand. The indicated reduction in total greenhouse gas emissions comes at an annual generation cost of $6.9 billion, which is an increase of 16.01% over the estimated baseline cost, and the solution uses over 99.99% of the $15 billion allotted for capital investment.

Under this scenario, coal remains the dominant source of electricity in the region even though emissions are being minimized. 28 of the 31 coal plants continue to operate at full baseline capacity, two plants are scaled back, and one plant is shut down completely. At the same time, however, the use of renewable energy increases greatly. 20 of the 31 coal plants implement some amount of biomass co-fire, utilizing the entire amount of biomass available within the region, and this provides 7.15% of the total MWh generated in the region. The capital investment cost for this biomass co-fire capability is only 1.13% of the total capital investment, but the use of biomass leads to a reduction in 10.92% of the emissions from coal plants over baseline levels.

Wind accounts for 2.59% of generation in this scenario, with the development of 116 wind farms at a cost of $7.79 billion. The remaining $7.05 billion of capital investment is allocated to solar farm development at 73 locations, which accounts for 1.17% of generation. Through the addition of biomass co-fire and new wind and solar farms, the total amount of energy derived from renewable sources in the region increases from 3.37% to 14.20% in this scenario. Over half of this increase was due to the implementation of biomass-coal co-fire, and this reduction came at a fraction of the overall investment cost.

As for the non-coal facilities currently operating in the region, all biomass, co-fire, landfill, nuclear, water, and wind facilities operate at full capacity in this scenario, although two of the 13 gas facilities and 17 of the 22 oil facilities were shut down. These particular facilities, however, were among the least productive in the region and represented only 0.24% and 1.2% of total baseline generation, respectively.

4.3. Minimax scenarios

In order to examine the tradeoffs between minimizing cost and minimizing emissions, the results of the first two scenarios were used as the basis for applying the minimax criterion to the multi-objective optimization problem. Three additional scenarios are included here, to illustrate these tradeoffs: (1) equally-weighted cost and emissions objectives, (2) a double-weighted cost objective, and (3) a double-weighted emissions objective. The outcomes for these three scenarios are given in Table 7, and are generally in-line with expectations: the cost-weighted scenario uses less capital investment to develop fewer wind and solar sites, while the emissions-weighted scenario behaves in the opposite manner.

Fig. 3 provides an approximation of the efficient frontier for the overall multi-objective optimization problem, based on the five scenarios analyzed with this model. Point 1 on the graph represents the results of the Minimize Emissions scenario and Point 5 represents the Minimize Cost scenario. The three minimax scenarios are then used to provide representative examples of non-dominated, Pareto optimal solutions (Points 2, 3, and 4) that lie on the efficient frontier between the two extreme solutions.

The most interesting result from considering the three minimax scenarios is that they lead to between 11.79% and 13.16% of generation being derived from renewable sources. Even in the cost-weighted scenario, the corresponding value is much greater than the 5.73% achieved in the Minimize Cost scenario. Much of this increased renewable generation is due to the utilization of at least 86.02% of available biomass in each of these three scenarios. The increased biomass use also provides for greatly reduced emissions of greenhouse gases when compared to the Minimize Cost scenario.

Of the 203 possible wind farm sites, 72 were selected in all five scenarios, with an average cost of $0.0720/kWh per site. The model did not select 87 of the possible sites in any of the five scenarios, and these sites have an average cost of $0.2246 per kWh generated. As for the possible solar farm sites, only 5 of the 477 were selected in each of the five scenarios. These sites average $0.1063 per kWh generated, as opposed to the $0.2407

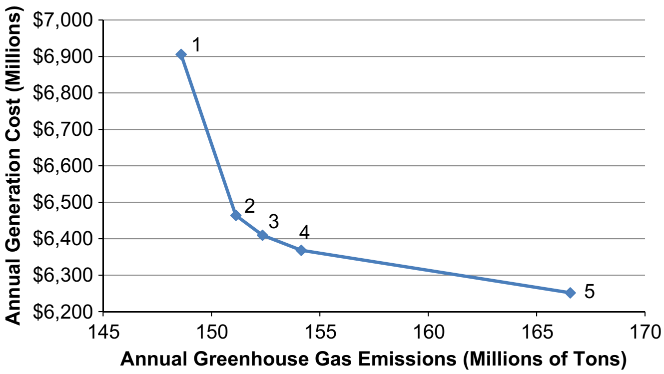


Fig. 3. Approximation of the efficient frontier for optimization model scenario results. Optimization scenarios—1: minimize emissions, 2: minimax—emissions weighted, 3: minimax—equal weight, 4: minimax—cost weighted, 5: minimize cost.

for the 404 sites never selected in any iteration of the model. These results point to the fact that although there are additional wind and solar farm installations possible within the region, the cost-effectiveness of many of these sites negates their possible benefits at this time. Unless the cost of renewable energy technologies continue to decrease, or more accurate assessments of the costs at these locations show a lower cost of generation, then many of the possibilities within this region should not be utilized due to the cost of generation in relation to other sites and sources in the region.

5. Conclusions

The model described here was designed to be flexible enough to be adjusted for use in regions other than just the greater southern Appalachian mountains. It thus supports incorporating additional renewable energy sources, such as offshore wind farms or building dedicated biomass facilities, or removing sources that may not be feasible in a given region. As a significant component of this flexibility, changes can also be made to existing sources of electricity generation within the region, as well as to any of the parameters in each of the calculations, without compromising the mathematical integrity of the underlying model.

Arnette and Zobel [31] provide a good example of how one might leverage such flexibility by using a version of the model to explore the regional impact of three different public policies: a renewable portfolio standard (RPS), a renewable energy production tax credit (REPTC), and a carbon tax (CT). The implementation of the RPS can be handled through the creation of an additional modeling constraint requiring that a specified percentage of total generation must come from renewable sources. As each RPS varies, this constraint can be altered based on the RPS level, the types of sources that count towards that RPS, and the amount of credit applied to each source, among other factors. In contrast, the application of the REPTC or CT policies can be handled entirely through modifications of the cost objective function in the model, since both of these directly impact the cost of generating electricity, either through the reduction of costs associated with renewable sources or by increasing the cost of fossil fuel generation.

The model shares many features with the Regional Energy Deployment System (ReEDS) model developed by NREL [6], and some of the input parameters and calculations related to cost were derived or adapted from this ReEDS model. However, it also differs from ReEDS in a number of key ways. First of all, the ReEDS model has only a single objective function related to cost, while the model described above features two competing objective functions: one for cost and one for emissions. Secondly, the model introduced above features a constraint for capital investment, and seeks to achieve the best results possible subject to a limit on capital investment spending. Thirdly, this new model allows for the creation of photovoltaic solar farm installations and the implementation of biomass/coal co-fire, neither of which are currently implemented in the ReEDS model. Finally, the model allows for costly or heavily polluting plants to be closed in order to minimize the values of the objective functions.

The results described above indicate that the cost of utilizing renewable energy sources at many locations may not be as prohibitive as once thought. As new sources of renewable energy are introduced into a region, or as public policies are implemented which impact the cost of electricity generation from either renewable sources or fossil fuels, the model outlined in this paper provides an adaptable framework which can be altered to reflect that new reality. By providing an approach for comparing a variety of different policies with respect to both cost and emissions, we can ultimately provide more comprehensive support for strategic decision making in this important area of public concern.

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